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A sensing array system with
image statistics processing

Pi-Fuay Chen

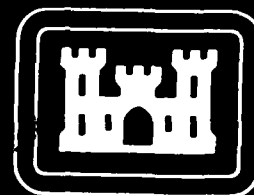
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PREFACE

This study was conducted under DA Project 4A161102B52C, Task B, Work Unit 0012, "Electronic Image Analysis for Feature Extraction."

The study was done under the supervision of Dr. F. Rohde, Team Leader, Center for Theoretical and Applied Physical Sciences; and Mr. M. Crowell, Jr., Director, Research Institute.

COL Edward K. Wintz, CE was Commander and Director and Mr. Robert P. Macchia was Technical Director of the Engineer Topographic Laboratories during the study period.



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A SENSING ARRAY SYSTEM WITH IMAGE STATISTICS PROCESSING

INTRODUCTION

A semiautomated technique for extracting a selected set of cartographic features such as road intersections, straight-line roads, and rectangular objects from aerial photographic imagery using Walsh transform was recently reported.^{1,2} An effort to extract and recognize another set of selected area cartographic features such as water, forest, city, field, and farmland with a spatial domain approach is described. The purpose of this work was to investigate and verify the performance of an automated apparatus for feature extraction using available off-the-shelf components. This apparatus can be used for features from photographic as well as radar imagery. The images which were used in this study were aerial photographs taken from two locations.

Among many available image spatial domain processing techniques, the image histogram and the image texture, which make use of first and second order image statistics, respectively, were considered for implementation. The hardware system consists of a 32- by 32-element solid-state array to convert cartographic images into electronic signals, a minicomputer to process the electronic signals from the array using a controlled software, and a computer-controlled two-dimensional translation stage as the image holder. The image statistical processing technique is implemented as a software for the system.

A brief system description is followed by a discussion on the selection of a feature vector from both image histogram and image texture methods. Although many components of the feature vector were calculated for each incoming test image, only four components were used for classification purposes. Classification was based on two types of classifiers with optical (aerial) imagery as test input. It was found that both classification methods resulted in a recognition accuracy of better than 90 percent. Finally, conclusions are given.

¹P.F. Chen and W.W. Seemuller, *Signal Signature of Topographic Features Using Analog Technology*, ETL Report No. 0185, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, Va., May 1979, AD-A076 110.

²J.R. Singleton and P.F. Chen, *Detecting Line Road and Road-Intersection Patterns at Various Angles*, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, Va., ETL-0274, October 1981.

SYSTEM DESCRIPTION

The block diagram of the system is shown in figure 1. A 9- by 9-inch transparency is illuminated by a white light source, and a section of the image is projected onto a Reticon 32- by 32-element solid-state array through an imaging lens. The array converts the optical energy of the image into a video signal. The video signal is quantized into 10 bits of digital signals, and the latter are sent to the Hewlett-Packard 2108 minicomputer for processing. The computer first takes in the quantized signals of 32 by 32 pixels of 1,024 gray levels array. With the brightest and darkest pixels within a frame as the maximum and minimum, this quantized image array is next scaled down to become 32 by 32 pixels of 16 gray levels. The histogram and joint probability matrix are then obtained using the scaled array as the input. The next step is to compute a feature vector based on the histogram and the joint probability matrix separately. Although 16 components of the feature vector were computed, only 4 components are used for classification of the selected cartographic features from optical imagery. Either a sequential template-matching classifier or a minimum-distance classifier is used to classify the input images into one of the preassigned image categories, or it is recognized as a reject if it does not belong to any of these categories. The classification result is then indicated on the CRT console. At the end of classification a signal is sent to the translational stage controllers to move the stages in the predetermined x and y positions, and a new section of image is projected onto the surface of the solid-state array. This procedure repeats itself until all preselected image sections are classified. The software for the classifiers is listed in the appendix.

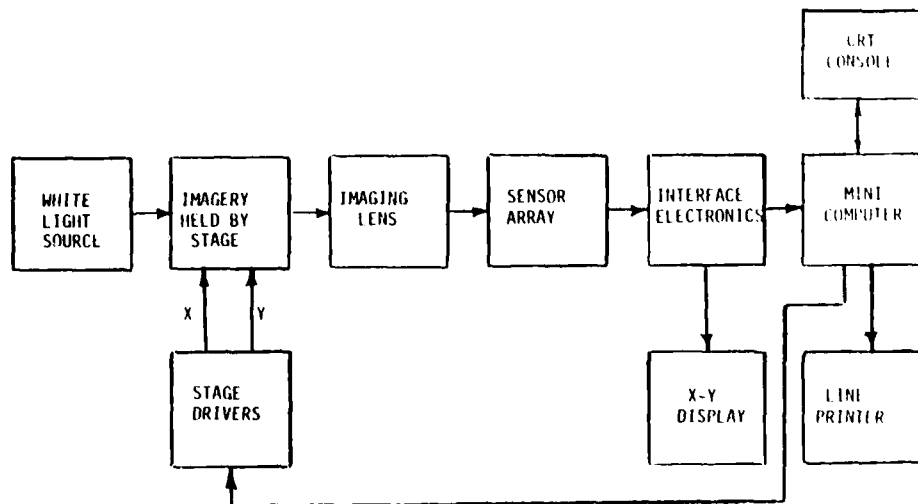


FIGURE 1. System Block Diagram.

FEATURE VECTOR SELECTION

Many publications are available on the image statistics processing techniques.* The most concise form of the feature vector based on the first- and second-order image pixel amplitude distribution was given by Pratt.³ He defined a discrete image array, $F(j, k)$, and the first-order probability distribution of image amplitude of a measurement window centered about (j, k) as

$$P(b) = \frac{N(b)}{M} \quad (1)$$

where M represents the total number of pixels in the measurement window, $N(b)$ is the number of pixels of amplitude b in the window, and $0 \leq b \leq L - 1$, and L is the number of gray levels of $F(j, k)$. The following measures have been formulated by Pratt as a concise means of describing the shape of first-order image histograms:⁴

$$\text{Mean} \quad \bar{b} = \sum_{b=0}^{L-1} b P(b) \quad (2)$$

$$\text{Variance} \quad \sigma_b^2 = \sum_{b=0}^{L-1} (b - \bar{b})^2 P(b) \quad (3)$$

$$\text{Skewness} \quad b_s = \frac{1}{\alpha_b^3} \sum_{b=0}^{L-1} (b - \bar{b})^3 P(b) \quad (4)$$

$$\text{Kurtosis} \quad b_k = \frac{1}{\alpha_b^4} \sum_{b=0}^{L-1} (b - \bar{b})^4 P(b) - 3 \quad (5)$$

*See Pratt, Haralick, Sutton, and Duda in the Bibliography for sources of information on this topic.

³W.K. Pratt, *Digital Image Processing*, John Wiley and Sons, Inc., New York, 1978.

⁴Ibid.

$$\text{Energy} \quad b_N = \sum_{b=0}^{L-1} [P(b)]^2 \quad (6)$$

$$\text{Entropy} \quad b_E = - \sum_{b=0}^{L-1} P(b) \log_2 [P(b)] \quad (7)$$

The second-order histogram features are based on the definition of the joint probability distribution of pairs of pixels. Haralick et al. have proposed a number of texture measures based on the joint amplitude histogram of pairs of geometrically related image points.⁵ Pratt stated that the two-dimensional histogram can be considered as an estimate of joint probability distribution. Consider a pair of pixels $F(j, k)$ and $F(m, n)$ that are separated by γ radial units, at an angle θ with respect to the x-axis of the measurement window. The histogram estimate of the second-order distribution is given by Pratt as⁶

$$P(a, b) = \frac{N(a, b)}{M} \quad (8)$$

where M is the total number of all occurrences in the measurement window, and where $N(a, b)$ is the number of occurrences for which $F(j, k) = a$, $F(m, n) = b$. The following are the texture measures that were used in this study:^{7,8}

$$\text{Mean:} \quad \bar{a} = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} a P(a, b) \quad (9)$$

$$\bar{b} = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} b P(a, b) \quad (10)$$

⁵R.M. Haralick, K. Shanmugan, and I. Dinstein, *Texture Features for Image Classification*, IEEE Transactions on Systems, Man, and Cybernetics, SMC-3, November 1973.

⁶W.K. Pratt, *Digital Image Processing*, John Wiley and Sons, Inc., New York, 1978.

⁷Ibid.

⁸R.M. Haralick, K. Shanmugan, and I. Dinstein, *Texture Features for Image Classification*, IEEE Transactions on Systems, Man, and Cybernetics, SMC-3, November 1973.

$$\text{Variance: } V_a = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} (a - \bar{a})^2 P(a, b) \quad (11)$$

$$V_b = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} (b - \bar{b})^2 P(a, b) \quad (12)$$

$$\text{Covariance: } C_o = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} (a - \bar{a}) (b - \bar{b}) P(a, b) \quad (13)$$

$$\text{Autocorrelation: } A_u = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} a b P(a, b) \quad (14)$$

$$\text{Absolute Value: } A_b = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} |a - b| P(a, b) \quad (15)$$

$$\text{Energy: } E_g = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} [P(a, b)]^2 \quad (16)$$

$$\text{Inverse Difference: } I_d = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} \frac{P(a, b)}{1 + (a - b)^2} \quad (17)$$

$$\text{Inertia: } I_n = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} (a - b)^2 P(a, b) \quad (18)$$

$$\text{Entropy: } E_n = - \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} p(a, b) \log_2 [P(a, b)] \quad (19)$$

For our application the joint probability matrix was made to be symmetrical so that $\bar{a} = \bar{b}$, and $V_a = V_b$. The variation of $P(a, b)$ due to different values of θ was not treated in this report, since $\theta = 0$ degree provided sufficiently separable feature vector for all the image categories considered. Each input image was first scaled down to 1,024 pixels of 16 gray levels ($L = 16$). Fifteen components for the feature vector based on equations (1) through (19) were then computed. It was discovered that only a measure from the first-order histogram, two measures from the second-order statistics (texture), and a measure of the number of array elements above the threshold value (NAEATV) were needed for classification purposes.

CLASSIFIER DESIGN

For the selected set of imagery, only three components of the feature vector computed in the previous section plus an NAEATV measure were required to constitute a 4-dimensional classifier. These components of the feature vector are as follows:

1. Skewness (Histogram)
2. Covariance (texture)
3. Autocorrelation (texture)
4. The number of array elements above the threshold value (NAEATV)

Two types of classifier, a sequential template-matching classifier and a minimum-distance classifier, were chosen for this purpose.

Sequential Template-Matching Classifier. In order to determine the upper and lower limits of the template values for each image category, many prototypes were obtained from imagery. Figure 1 shows the template ranges for each component of the feature vector selected for classifying the selected set of imagery. Six template ranges for the covariance were designated as follows: water, -1.0 to 2.25; field, 0 to 3.5; forest, 1.0 to 4.0; city, 4.0 to 9.0; farmland, 9.0 to 20.0; and not recognized, above 20.0. The template ranges for the autocorrelation were assigned: forest, 0 to 90; field, 70 to 300; and water, 90 to 300. For discriminating "forest" from "field," the template ranges of the skewness were chosen as field, -10 to 0, and forest, above 0 to 5. Likewise, the template ranges for the NAEATV were set to be water, 0 to 300 and field, 301 to 1023. It is noticed that many template ranges overlap one another; however, with the sequential template-matching scheme discussed next, most of the images tested so far have been recognized or classified correctly.

The computed covariance of the unknown incoming input image is first compared to the template range of the covariance. If it is within the range of -1.0 to 2.25, it is temporarily assumed to be in the category of "water." The next step is to examine whether the autocorrelation of the unknown image is in the range of 90 to 300 or not. If it is in that range, the NAEATV of the unknown image is tested against its corresponding template range. If it falls in between the range of 0 to 300, the unknown image is classified as "water."

If any one of the previously described tests is negative, the unknown image is temporarily assumed to be in the category of "field." Just as in the tests performed for the category of "water," the covariance, autocorrelation, skewness, and NAEATV of the unknown image are now sequentially compared to their corresponding template ranges (see FDCN2, appendix A). If all tests are true, the unknown image is classified as "field." If any one of these four steps is false, the unknown image is temporarily reassigned to the category of "forest."

Likewise, the unknown image has to go through three sequential tests in this assumed category for its covariance, autocorrelation, and skewness. The strategy is just as stated before. If all the tests are true, the unknown is classified as "forest" or it is reassigned to the next category of image, and so on. It is noticed that only a single covariance comparison is needed for the categories of "city" and "farmland" (see FDCN2, appendix A). Finally, if the unknown image does not belong to any stage of the tests described above, it is then classified as "not recognized."

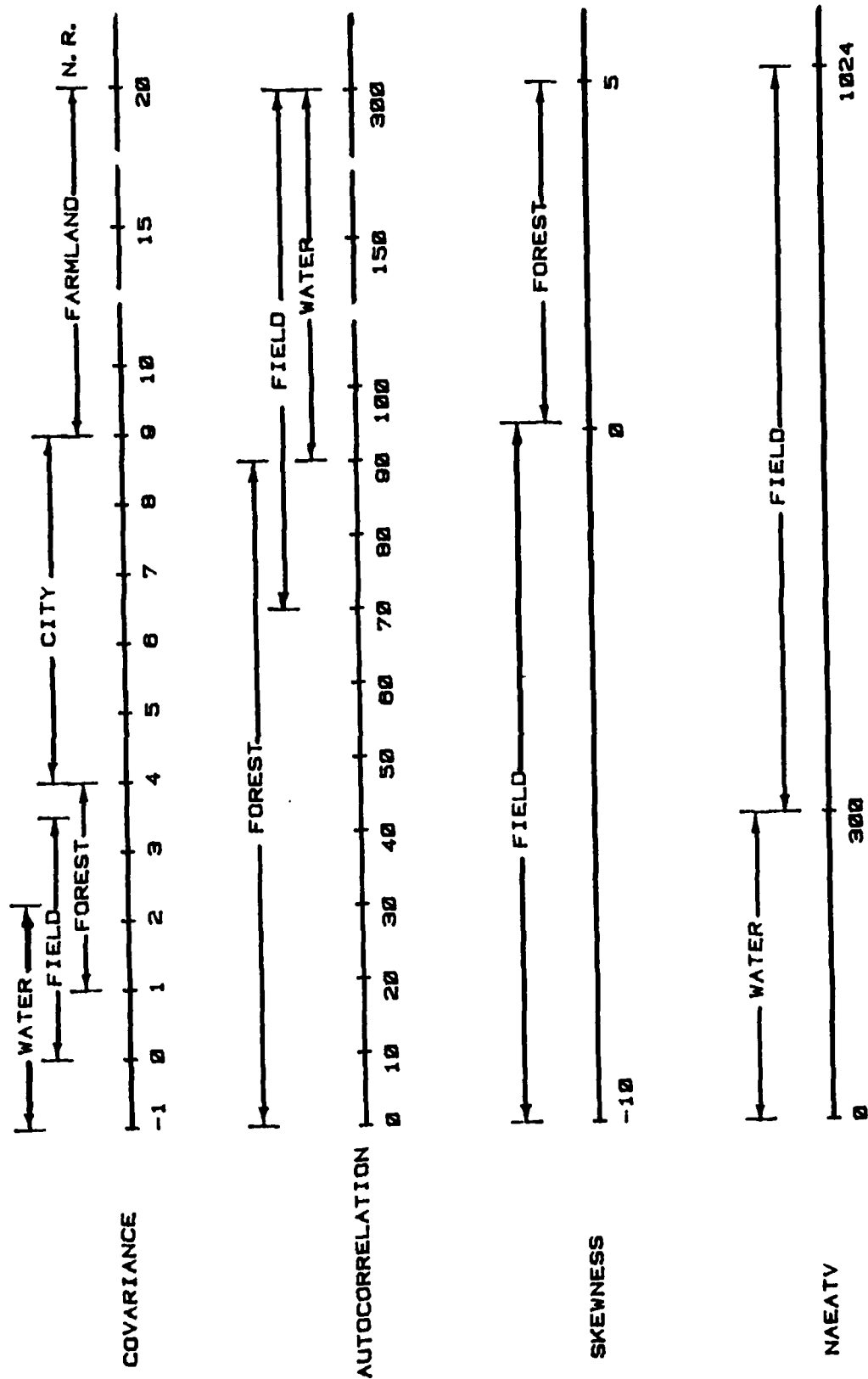


FIGURE 2. Template Ranges for Feature Vector Used for Classification.

Minimum-Distance Classifier. Assuming that the image categories of interest (or the classes to which the input imagery are to be classified) are represented by prototypes (or reference patterns) $\underline{Z}_1, \underline{Z}_2, \dots, \underline{Z}_m$, the Euclidean distance between an arbitrary vector of unknown classification, \underline{X} and the i -th prototype is given by

$$D_i = \|\underline{X} - \underline{Z}_i\| = \sqrt{(\underline{X} - \underline{Z}_i)^T (\underline{X} - \underline{Z}_i)} \quad (20)$$

where $(\underline{X} - \underline{Z}_i)^T$ is the transpose of $(\underline{X} - \underline{Z}_i)$. A minimum distance classifier computes the distance from a pattern \underline{X} of unknown classification to the prototype of each category and assigns the pattern to the category to which it is closest. In other words, \underline{X} is assigned to category "i" if $D_i < D_j$ for all $j \neq i$.

To establish the prototypes $\underline{Z}_1, \underline{Z}_2, \dots, \underline{Z}_m$, the components of the feature vector — "covariance" and "autocorrelation" (computed from the joint probability matrix), the component "skewness" (evaluated from the first-order histogram), and "NAEATV" were used. They are expressed as

$$\underline{Z}_i = [(\text{COV})_i, (\text{AU})_i, (\text{NAEATV})_i, (\text{SKEW})_i]^T \quad (21)$$

The required five prototypes, one for each image category of interest, i.e., city, field, farmland, forest, and water, were obtained by using the mean value of these four components computed from many image samples. These \underline{Z}_i were then used to compute D_i and classify the incoming unknown pattern \underline{X} .

The feature vector components "autocorrelation" and "NAEATV" are approximately 10 and 100 times larger than the other two components for all five image categories considered. In order for the smaller components not to be overpowered by these two large components in classification computation, "autocorrelation" and "NAEATV" were divided by factors of 10 and 100 respectively. Likewise the corresponding components of the feature vector of the unknown incoming pattern \underline{X} are also normalized in the same way before being submitted to the classifier for computation. Figure 3 shows the final components for the prototypes used for this classifier.

	CITY	FIELD	FARMLAND	FOREST	WATER
COVARIANCE	7. 197	0. 895	13. 70	2. 906	0. 360
AUTO-CORRELATION	4. 076	18. 12	9. 003	6. 556	17. 70
NAEATV	5. 311	10. 23	6. 360	1. 020	0. 0048
SKEWNESS	2. 890	-1. 078	1. 285	0. 940	-5. 760

FIGURE 3. Prototypes for Minimum-Distance Classifier.

TEST RESULTS

A set of high quality, 1 to 20,000 scale, aerial photoimagery from Baltimore, Maryland, and Pittsburgh, Pennsylvania, consisting of image categories such as city (combination of commercial and residential structures, DLMS category number 504 FIC 301 and DLMS category number 505 FIC 401), field (agriculture field used primarily for crop and pasture lands, DLMS category number 510 FIC 950), farmland (cropland, DLMS category number 510 FIC 950), forest (deciduous, DLMS category number 510 FIC 952), and water (river and inlet to bay, smooth fresh water, DLMS category number 501 FIC 941) was used for this experimentation. Figures 4(a) to 8(a) show the line printer output of the typical image categories: city, field, farmland, forest, and water, respectively. Each is printed in 16 gray shades by line-printing.

In figures 4(b) through 8(b), the 16 components of the typical feature vector computed by using equations 1 to 19 and the "NAEATV" are shown for each image category. It was found that only the components "covariance" and "autocorrelation," evaluated on the basis of image texture, and the "skewness," computed from image histogram, are relatively separable for all the image categories considered. Therefore, these components together with the "NAEATV" were chosen to constitute a four-dimensional classifier for both the sequential template-matching and the minimum-distance classification schemes.

Approximately 120 image sections (for all 5 classes) were randomly scanned and were provided as the input test imagery for evaluating the classification accuracy for both classification methods. The results are illustrated in figures 9 and 10. Approximately 92 percent overall classification accuracy was obtained for the sequential template-matching classifier. The overall classification accuracy for the minimum-distance classifier is relatively higher and in the range of about 97 percent. The results presented above are valid for high quality aerial photoimages. The images were taken from the same aircraft altitudes, but covered two different geological areas. Various parameters such as image quality, scale changes, resolution, season and geological formation were not addressed.

The same experimental setup was used to extract and classify a set of radar imagery with modified classifiers (different feature vector, template range, and prototypes). Approximately 90 percent recognition accuracy was obtained for this selected set of radar imagery. This effort will be reported in another research note.

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FOREST

SECOND ORDER STATISTICS

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SUM OF PROBABILITY= 1.000
MEAN= 7.981
VARIANCE= 4.807
COVARIANCE= 3.40185
ENERGY= .05609
INVERSE DIFFERENCE= .58190
ENTROPY= 3.55456
INERTIA= 2.81049
ABSOLUTE VALUE= 1.12702
AUTOCORRELATION= 67.09576
NO. OF ELEMENTS>IT= 85
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LIST

HISTOGRAM STATISTICS

SUM HISTOGRAM= .9980
MEAN OF HISTOGRAM= 7.8691
VARIANCE OF HISTOGRAM= 5.1783
ENERGY OF HISTOGRAM= .1615
SKEWNESS OF HISTOGRAM= .6354
KURTOSIS OF HISTOGRAM= 4.1685
ENTROPY OF HISTOGRAM= 2.0555

(b)

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(a)

FIGURE 7. (a) Pictorial Print of Input Image, and (b) Feature Vector for Forest.

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WATER

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SECOND ORDER STATISTICS
SUM OF PROBABILITY= 1.000
MEAN= 14.209
VARIANCE= 1.542
COVARIANCE= .30222
ENERGY= .23814
INVERSE DIFFERENCE= .78391
ENTROPY= 1.84030
INEHTIA= 2.47984
ABSOLUTE VALUE= .63710
AUTOCORRELATION= 202.18854
NO. OF ELEMENTS>IT= 0
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WATER

HISTOGRAM STATISTICS
SUM HISTOGRAM= .9873
MEAN OF HISTOGRAM=13.8770
VARIANCE OF HISTOGRAM= 2.5811
ENERGY OF HISTOGRAM= .4393
SKEWNESS OF HISTOGRAM=-6.4336
KURTOSIS OF HISTOGRAM=21.2298
ENTROPY OF HISTOGRAM= .9716

(b)

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WATER

[illegible]

(a)

FIGURE 8. (a) Pictorial Print of Input Image, and (b) Feature Vector for Water.

CLASSIFIED CATEGORY

	CITY	FIELD	FARMLAND	FOREST	WATER	NOT RECOGNIZED
CITY	18	0	1	1	0	0
FIELD	0	25	0	2	0	0
FARMLAND	1	0	20	0	0	1
FOREST	1	0	0	19	0	2
WATER	0	0	0	0	20	1

TRUE IMAGE CATEGORY

NUMBER OF OVERALL IMAGES: 110
 NUMBER OF OVERALL CORRECT CLASSIFICATION: 102
 PERCENTAGE OF OVERALL CORRECT CLASSIFICATION: 92.72

FIGURE 9. Classification Results for Sequential Template-Matching Classifier.

CLASSIFIED CATAGORY

TRUE IMAGE CATAGORY	CLASSIFIED CATAGORY					
	CITY	FIELD	FARMLAND	FOREST	WATER	NOT RECOGNIZED
CITY	25	0	0	0	0	0
FIELD	0	23	0	1	1	0
FARMLAND	0	0	25	0	0	0
FOREST	0	0	0	25	0	0
WATER	0	0	0	1	24	0

TRUE IMAGE CATAGORY

NUMBER OF OVERALL IMAGES: 125
 NUMBER OF OVERALL CORRECT CLASSIFICATION: 122
 PERCENTAGE OF OVERALL CORRECT CLASSIFICATION: 97.6

FIGURE 10. Classification Results for Minimum-Distance Classifier.

CONCLUSIONS

1. Statistical processing of photographic images in spatial domain provides a convenient means for evaluating image texture and coarseness of area features.
2. The technique is most applicable for extracting and classifying if the search window contains only a single category of cartographic features such as city, forest, field, water, or farmland.
3. Better than 90 percent classification accuracy was obtained for both the sequential template-matching classifier and the minimum-distance classifier for a set of approximately 120 selected aerial photographic images.
4. With modified feature vector, template ranges, and prototypes, the method can also be applied to extract and classify radar images.
5. The scheme may produce ambiguous results when the search window contains more than a single category of cartographic area features.

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APPENDIX A. Computer Printouts FDCN2 and FDCN4

LFDCN2 I=00004 IS ON CR00009 USING 00003 BLKS R=0000

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0001 FIN4,L
0002 C
0003 C***** SUBROUTINE FDCN2 -- REV 03/20/81 *****
0004 C
0005 C
0006 C SUBROUTINE TO PERFORM FEATURE CLASSIFICATION FOR PROGRAM
0007 C
0008 C TXIR7
0009 C
0010 C
0011 SUBROUTINE FDCN2(ITS,COV,AU,SKW,LUOT)
0012 IF(COV LT -1 OR COV GT 2 25) GOTO 810
0013 IF(AU LT 90 OR AU GT 300) GOTO 810
0014 IF(ITS LT 0 OR ITS GT 300)GOTO 810
0015 WRITE(LUOT,80)
0016 GOTO 888
0017 810 IF(COV LT 0 OR COV GT 3 50) GOTO 820
0018 IF(AU LT 70 OR AU GT 300)GOTO 820
0019 IF(SKW LT -10 OR SKW GT 0) GOTO 820
0020 IF(ITS LT 300 OR ITS GT 1024) GOTO 820
0021 WRITE(LUOT,81)
0022 GO TO 888
0023 820 IF(COV LT 1 00 OR COV GT 4 0) GOTO 830
0024 IF(AU LT 0 OR AU GT 90)GO TO 830
0025 IF(SKW EQ 0 OR SKW GT 5) GOTO 830
0026 WRITE (LUOT,82)
0027 GO TO 888
0028 830 IF(COV LT 4 0 OR COV GT 9 0) GOTO 835
0029 WRITE(LUOT,83)
0030 GOTO 888
0031 835 IF(COV LT 9 0 OR COV GT 20)GOTO 840
0032 WRITE(LUOT,85)
0033 GOTO 888
0034 840 WRITE(LUOT,84)
0035 GOTO 888
0036 80 FORMAT(IX,"WATER")
0037 81 FORMAT(IX,"FIELD")
0038 82 FORMAT(IX,"FOREST")
0039 83 FORMAT(IX,"CITY ")
0040 84 FORMAT(IX,"THIS CARTOGRAPHIC FEATURE IS NOT SPECIFIED")
0041 85 FORMAT(IX,"FARMLAND")
0042 888 IF(LUOT EQ 6)WRITE(LUOT,880)
0043 880 FORMAT("1")
0044 RETURN
0045 END
0046 END$

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APPENDIX A. Continued

8FDCH4 I=00004 IS ON CR00009 USING 00005 BLKS R=0000

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0001 FTH4
0002 C===== SUBROUTINE FDCN4 =====
0003 C=
0004 C=          MINIMUM DISTANCE CLASSIFICATION SUBPROGRAM
0005 C=
0006 C=
0007 C=          WRITTEN 04/28/81
0008 C=          RECOPIED 07/22/81
0009 C=====
0010 SUBROUTINE FDCN4(COV,AU,ITS,SKW,LUOT)
0011 DIMENSION COVR(7),ACORR(7),ITSRR(7),SKWR(7),DIS(7)
0012 DATA COVR/7 197.0 895.13 70.2 906.0 36/
0013 DATA ACORR/40 76.181 2.90 03.65 56.177 0/
0014 DATA ITSRR/531,1023,636,102,0/
0015 DATA SKWR/2 80,-1 078.1 285.0 94.-5 76/
0016 LUOT=1
0017 NUM=5
0018 ACOR=AU/10 0
0019 ITSS=ITS/100
0020 600 DO 610 I=1,NUM
0021 C=(COVR(I)*2+(ACORR(I)/10)*2+(ITSRR(I)/100)*2
0022 I+(SKWR(I)+10)*2)/2
0023 DIS(I)=(COV*COVR(I)+ACOR*(ACORR(I)/10)+ITSS*ITSRR(I)/100
0024 I+(SKW*10)*(SKWR(I)+10))-C
0025 610 CONTINUE
0026 ICLAS=1
0027 BIGD=DIS(1)
0028 DO 620 J=2,NUM
0029 IF(DIS(J) GT BIGD) ICLAS=J
0030 IF(DIS(J) GT BIGD) BIGD=DIS(J)
0031 620 CONTINUE
0032 GO TO (630,640,650,660,670) ICLAS
0033 630 WRITE(LUOT,631)
0034 GOTO 800
0035 640 WRITE(LUOT,641)
0036 GOTO 800
0037 650 WRITE(LUOT,651)
0038 GOTO 800
0039 660 WRITE(LUOT,661)
0040 GOTO 800
0041 670 WRITE(LUOT,671)
0042 GOTO 800
0043 631 FORMAT("CITY")
0044 641 FORMAT("FIELD")
0045 651 FORMAT("FARMLAND")
0046 661 FORMAT("FOREST ")
0047 671 FORMAT("WATER ")
0048 800 IF(LUOT EQ 6) WRITE(LUOT,850)
0049 850 FORMAT("I")
0050 RETURN
0051 END
0052 ENDS

```

L MED
-8